ACCURACY EVALUATION OF SATELLITE-BASED LAND COVER DATA TO SUPPORT WATER RESOURCE MANAGEMENT IN MANGGARAI REGENCY

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Abstract: To support sustainable water resource management in Manggarai Regency, the availability of accurate land cover data is essential. However, the limited availability of local data necessitates the use of satellite imagery-based data, such as ESRI and Landsat 8 imagery. This study aims to evaluate the accuracy of both datasets before they are used in land cover analysis. The 2024 ESRI imagery, which has been pre-classified into eight land cover classes, was compared with 2024 Landsat 8 imagery, which was classified using the Maximum Likelihood Classification (MLC) method in ArcGIS into ten land cover classes. Accuracy assessment was conducted using the Accatama plugin in QGIS, with Google Earth Pro serving as the reference data. The number of samples was determined using Slovin's formula, resulting in 488 samples for the ESRI imagery and 951 for Landsat 8. The evaluation results show that ESRI imagery achieved a higher accuracy (0.72) compared to Landsat 8 (0.19). These findings suggest that ESRI imagery is more appropriate for land cover analysis aimed at enhancing water resource management efforts in Manggarai Regency. Although some classification errors still occurred, the ESRI imagery generally provides a more accurate representation of land cover conditions in the study area.

Keywords: *Land Cover Classification, Satellite Imagery, Accuracy Assessment, ESRI Imagery*

INTRODUCTION

Reliable land cover data serves as a crucial foundation for managing water resources sustainably, particularly in ecologically fragile and topographically varied regions like Manggarai Regency. Changes in land cover, especially the shift toward dryland farming and urban development, significantly alter hydrological patterns by reducing infiltration, increasing runoff, and intensifying erosion, thus challenging long-term flood mitigation and water management efforts (Yulianto et al., 2020).

The absence of consistently updated local land cover data often results in dependence on satellite imagery. Remote sensing has emerged as a cost-effective and efficient alternative due to its broad spatial coverage and frequent updates. Landsat 8, for instance, provides moderate-resolution multispectral data suitable for land cover classification and is widely used in developing regions due to its free accessibility (Roy et al., 2014). Still, the accuracy of classifications depends on the processing method used, particularly the choice of algorithm and the quality of reference data (Wang et al., 2022)

Recent improvements in land cover classification have been driven by the application of machine learning (ML) and deep learning (DL) techniques. Algorithms such as Random Forest (RF) and Support Vector Machine (SVM) have demonstrated reliable accuracy for various land cover types, especially when ground reference data is available for training and validation (Talukdar et al., 2020). Meanwhile, global land cover datasets like the ESRI Land Cover product are generated using high-resolution satellite imagery (10 m) and deep learning workflows, offering relatively high accuracy in diverse environments (Venter & Sydenham, 2021).

Despite their growing popularity, global land cover products still require local validation. Classification accuracy can vary significantly across different geographic and ecological settings, with performance often reduced in mountainous and fragmented landscapes (Grekousis et al., 2015). Therefore, comparative studies that evaluate the performance of different land cover sources in specific locations, like Manggarai, are needed.

Accuracy assessment tools such as the Accatama plugin in QGIS, combined with visual verification using Google Earth Pro, have been widely adopted to validate classified imagery at the local level (Tsendbazar et al., 2018). These tools facilitate point-based validation, helping assess whether land cover classifications are consistent with actual land use patterns.

This study aims to assess and compare the accuracy of two land cover datasets: (1) the 2024 ESRI Land Cover product and (2) Landsat 8 imagery classified using the Maximum Likelihood Classification (MLC) algorithm in ArcGIS. By evaluating their performance using ground-truth samples and standardized accuracy metrics, the research aims to determine which dataset is more suitable for land cover analysis in support of water resource management in Manggarai Regency.

METHOD

This study employed a quantitative, descriptive-comparative approach to evaluate the accuracy of two land cover datasets: ESRI Land Cover and Landsat 8 imagery classified using the Maximum Likelihood Classification (MLC) method in Manggarai Regency, Indonesia.

First, satellite images from 2024 were collected: Landsat 8 data from the USGS Earth Explorer, and ESRI Land Cover data from the ArcGIS Living Atlas. The study area covered the administrative boundary of Manggarai Regency, which includes diverse land cover types such as forest, agriculture, settlements, and water bodies.

The Landsat 8 imagery was classified using the MLC method in ArcGIS, producing 8 land cover classes. The ESRI imagery, already classified using cloud-based deep learning, included 8 land cover classes at 10-meter resolution. For comparison, the class names from both datasets were harmonized to match local land cover categories. To assess accuracy, ground truth points were created using visual interpretation in Google Earth Pro. The number of validation samples, 951 for Landsat and 488 for ESRI, was calculated using Slovin's formula, ensuring appropriate sample size based on the area.

Validation points were spread across the region and manually checked to represent real land cover conditions. Then, using the Accatama plugin in QGIS, confusion matrices were created to calculate accuracy for each dataset.

This process allowed a direct comparison of classification performance to determine which dataset is more suitable for land use planning and sustainable water resource management in the region.

RESULT

Land Cover Classification Results

Two land cover maps were produced for Manggarai Regency using two different satellite datasets: Landsat 8 and ESRI imagery. The Landsat 8 imagery was processed using the Maximum Likelihood Classification (MLC) method in ArcGIS, resulting in eight distinct land cover classes. These include clouds, dense forest, Crops, medium forest, mixed forest, Rangeland, Bare Ground, and Built Area. This classification encompasses a diverse range of land cover types, including both natural and anthropogenic features, as well as atmospheric elements such as clouds and shadows, which are commonly observed in optical satellite imagery.

Meanwhile, the ESRI satellite imagery, which had already been pre-classified using cloud-based deep learning algorithms, provided a land cover map with eight general classes: Water, Crops, Trees, Built Area, Clouds, Flooded Vegetation, Bare Ground, and Rangeland. The classification from ESRI imagery represents a simplified yet consistent depiction of land cover patterns, suitable for regional analysis and long-term monitoring.

To facilitate comparison between the two datasets, the thematic categories were harmonized. This process involved aligning the land cover classes from both datasets into a unified classification scheme that reflects the local context. For example, the various forest categories in the Landsat 8 map were grouped and adjusted to correspond to the broader vegetation class used in the ESRI classification. This harmonization ensured that the accuracy assessment and further analysis were conducted under a consistent framework.

Validation Sample Distribution

To evaluate the accuracy of the classification results, ground truth data were generated through visual interpretation of high-resolution imagery in Google Earth Pro. The number of validation points for each dataset was determined using Slovin's formula, which considers population size and a predefined margin of error to calculate an optimal sample size. A total of 951 validation points were collected for the Landsat 8 classification and 488 points for the ESRI classification.

The validation samples were spatially distributed across Manggarai Regency to ensure adequate representation of all land cover types, including forests, agricultural lands, urban settlements, and water bodies. Each point was manually interpreted and cross-verified to reflect the actual land cover conditions on the ground. This approach ensured that the reference data used in accuracy assessments were reliable and reflective of real-world conditions.

Classification Accuracy Assessment

Accuracy assessments were conducted using the Accatama plugin in QGIS. Confusion matrices were generated for both datasets to calculate standard accuracy metrics, including overall accuracy, and user's accuracy.

The classification result from the Landsat 8 imagery showed poor performance, with an overall accuracy of only 0.19. A significant number of misclassifications were found, particularly in the paddy field class, where 87 out of 100 validation samples were incorrectly classified. Most of these samples were misclassified as dense forest, medium forest, or other vegetated classes, while others were labeled as bare land, and clouds. These errors indicate a substantial degree of spectral confusion between rice fields and other vegetation types, a common challenge in multispectral satellite imagery. This high level of misclassification reduces the reliability of the Landsat 8 classification for detailed land cover mapping in complex environments such as Manggarai Regency.

In contrast, the ESRI dataset yielded considerably better results, achieving an overall accuracy of 0.72. Within the vegetation class, 23 misclassifications were identified, where a small number of samples were confused with shrub, paddy field, and water categories. However, 263 out of 286 samples in the vegetation class were correctly classified. These results demonstrate a higher degree of consistency and accuracy in the ESRI dataset, making it more suitable for spatial analysis and environmental planning applications in the region.

Visualization

Figure 1 illustrates the 2024 land cover classification map generated from Landsat 8 imagery. The map visualizes eight land cover classes, highlighting the spatial distribution of natural vegetation, agricultural lands, urban settlements, and cloud cover. However, classification inconsistencies, especially in paddy fields and cloud-influenced areas, are evident

Figure 2 displays the 2024 land cover classification map derived from the ESRI imagery. With eight clearly defined land cover classes, this map presents a more coherent spatial representation of land cover patterns across Manggarai Regency. The distinctions between trees, crops, built areas, and water bodies are more pronounced, providing a clearer basis for subsequent spatial and environmental analyses.

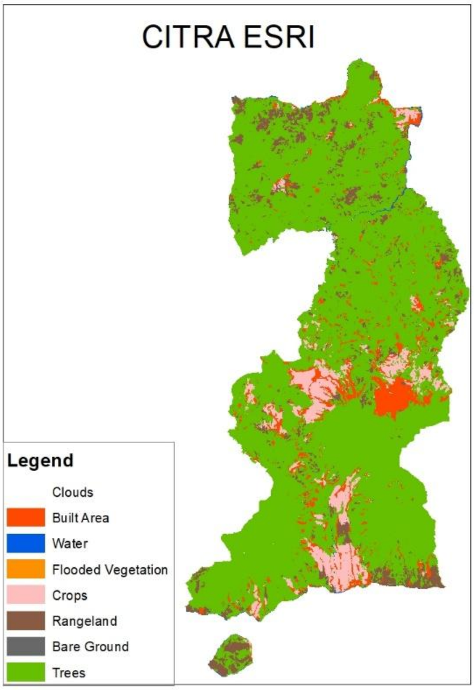

Figure 1. Citra ESRI

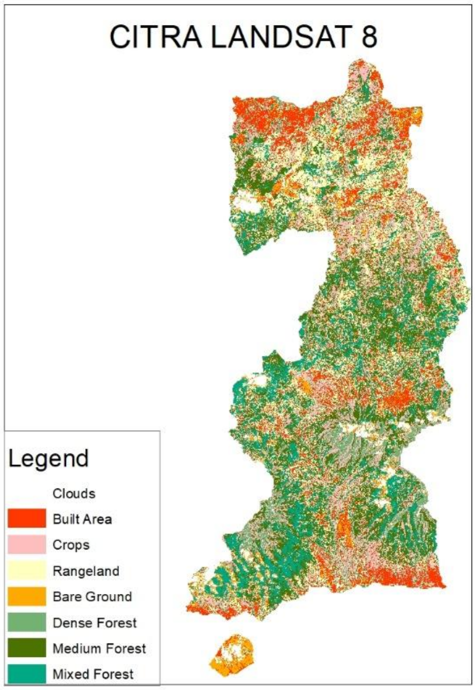

Figure 2. Citra Landsat 8

Accuracy Matrix Tables

Table 1 shows the confusion matrix for the ESRI classification. The table demonstrates a lower error rate and a greater number of correctly identified samples across most land cover categories. The findings support the use of the ESRI dataset as a more accurate and practical base map for land use planning, land cover change monitoring, and sustainable resource management in Manggarai Regency

Table 1. *Matriks Akurasi Citra* ESRI

Class	1	2	3	4	5	6	7	8	Total	*User Accuracy*
Water (1)	44	5	2	5	0	3	0	9	68	0.64
Teers (2)	2	77	0	3	0	3	0	15	100	0.77

Flooded Vegetation (3)	1	0	5	0	0	0	0	1	7	0.71
Crops (4)	0	5	1	66	0	3	1	22	98	0.67
Built Area (5)	1	14	3	12	24	9	0	35	98	0.24
Bare Ground (6)	3	0	0	0	0	3	0	1	7	0.43
Clouds (7)	0	6	0	3	0	0	0	3	12	0
Rangeland (8)	6	17	2	6	0	0	0		98	0.68
Total	57	124	13	95	24	21	1		153	488
Producer Accuracy	0.1	0.9	0	0.5	1	0	0			
						Overall Accuracy: 0.72				

Table 2 presents the confusion matrix for the Landsat 8 classification. The matrix summarizes the number of correctly and incorrectly classified validation points per land cover class. The results confirm a high level of misclassification, particularly within the agricultural and vegetated categories, which contributes to the overall low accuracy score.

Table 2. *Matriks Akurasi Citra* Landsat 8

Classes	1	2	3	4	5	6	7	8	Total	*User Accuracy*
Clouds (1)	14	150	4	43	22	12	1	8	254	0.10
Dense Forest (2)	2	30	6	26	25	2	0	7	98	0.31
Crops (3)	7	47	13	13	5	5	0	10	100	0.13

Medium Forest (4)	3	37	5	35	16	3	1	0	100	0.35
Mixed Forest (5)	8	10	5	21	31	7	2	16	100	0.31
Rangeland (6)	2	21	4	10	11	42	2	8	100	0.42
Built Area (7)	3	48	2	28	15	2	0	2	100	0
Bare Ground (8)	6	55	0	12	11	5	0	10	99	0.10
Total	40	398	39	95	188	136	6	61	951	488
Producer Accuracy	0.42	0.14	0.1	0.2	0.2	0.4	0	0		
					Overall Accuracy: 0.19					

DISCUSSION

The results of this study show a clear difference in classification performance between the two datasets. The Landsat 8 imagery, classified using the Maximum Likelihood Classification method, produced low accuracy, with an overall score of only 0.19. Misclassifications frequently occurred in paddy field areas, indicating spectral confusion with other vegetation types. This suggests that conventional classification methods are less effective in complex landscapes such as Manggarai Regency.

In contrast, the ESRI dataset, which uses cloud-based deep learning algorithms, demonstrated significantly better results, achieving an overall accuracy of 0.72. Its simpler yet consistent classification scheme enabled more reliable identification of land cover types. The harmonization of thematic classes between the two datasets allowed for valid comparison and highlighted the importance of adopting standardized classification frameworks. Overall, these findings suggest that satellite imagery processed with artificial intelligence offers a more effective alternative for land cover mapping, especially in support of land use planning and sustainable resource management in complex tropical environments.

CONCLUSION

This study demonstrates that the choice of satellite data and classification method significantly affects the accuracy of land cover mapping. The use of deep learning-based classification on pre-processed ESRI imagery resulted in higher reliability compared to traditional classification applied to Landsat 8 imagery. The harmonization of land cover categories further supported consistent comparison and analysis. These findings highlight the importance of adopting modern classification approaches and standardized frameworks for accurate, efficient, and sustainable land use monitoring in complex environments.

REFERENCES

Grekousis, G., Mountrakis, G., & Kavouras, M. (2015). An overview of 21 global and 43 regional land-cover mapping products. In *International Journal of Remote Sensing* (Vol. 36, Issue 21, pp. 5309–5335). Taylor and Francis Ltd. https://doi.org/10.1080/01431161.2015.1093195

Roy, D. P., Wulder, M. A., Loveland, T. R., C.E., W., Allen, R. G., Anderson, M. C., Helder, D., Irons, J. R., Johnson, D. M., Kennedy, R., Scambos, T. A., Schaaf, C. B., Schott, J. R., Sheng, Y., Vermote, E. F., Belward, A. S., Bindschadler, R., Cohen, W. B., Gao, F., … Zhu, Z. (2014). Landsat-8: Science and product vision for terrestrial global change research. *Remote Sensing of*

Environment, *145*, 154–172. https://doi.org/10.1016/j.rse.2014.02.001

Talukdar, S., Singha, P., Mahato, S., Shahfahad, Pal, S., Liou, Y. A., & Rahman, A. (2020). Land-use land-cover classification by machine learning classifiers for satellite observations-A review. In *Remote Sensing* (Vol. 12, Issue 7). MDPI AG. https://doi.org/10.3390/rs12071135

Tsendbazar, N. E., Herold, M., de Bruin, S., Lesiv, M., Fritz, S., Van De Kerchove, R., Buchhorn, M., Duerauer, M., Szantoi, Z., & Pekel, J. F. (2018). Developing and applying a multi-purpose land cover validation dataset for Africa. *Remote Sensing of Environment*, *219*, 298–309. https://doi.org/10.1016/j.rse.2018.10.025

Venter, Z. S., & Sydenham, M. A. K. (2021). Continental-scale land cover mapping at 10 m resolution over europe (Elc10). *Remote Sensing*, *13*(12). https://doi.org/10.3390/rs13122301

Wang, Z., Sui, L., & Zhang, S. (2022). Generating Daily Land Surface Temperature Downscaling Data Based on Sentinel-3 Images. *Remote Sensing*, *14*(22). https://doi.org/10.3390/rs14225752

Yulianto, F., Suwarsono, Nugroho, U. C., Nugroho, N. P., Sunarmodo, W., & Khomarudin, M. R. (2020). Spatial-Temporal Dynamics Land Use/Land Cover Change and Flood Hazard Mapping in the Upstream Citarum Watershed, West Java, Indonesia. *Quaestiones Geographicae*, *39*(1), 125–146. https://doi.org/10.2478/quageo-2020-0010